

Multi-Fractal Texture Segmentation for Off-Road Robot Vision Application

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ABSTRACT. *Multipermuted Multinomial Measures (MMM) are considered for characterizing outdoor images. First, we recall the Multi-fractal properties of MMM's and the basic principle of a method for the parameters estimation. Secondly, we apply this method to textures drawn from the Brodatz album so as to show the relevance of the model to texture representation. The next part exemplifies how different textures can be characterized by a set of several "scale-stable" parameters directly computed from the parameters. Final results are given on outdoor images.*

Keywords: Multipermuted Multinomial Measures; Texture Segmentation; Multifractal.

1. **Introduction.** Despite a huge literature on texture analysis, there is no general model for computing textures from raw data especially when some structural information must be taken into account. For instance, satellite images exhibit hierarchical man-made structures and statistical natural patterns which both share the property of self-similarity at several scales. In fact, outdoor images including trees, bush and trails may still exhibit some statistical estimates typical of self-similarity. Such a structural property may be easily injected within fractal concepts so as to provide a suitable tool for unifying data and structures. In this paper, we deal with some generalization of Multi-fractal measures for performing automatic segmentation of satellite and outdoor images. A seminal work on the generation of textures based on the fractional Brownian motion (fBm) is Pentland's[18]. For $t > 0$, a fBm with Hurst exponent $H(0 < H < 1)$ can be defined with respect to Brownian motion $B(t, \omega)$ as:

$$B_H(t, \omega) = \frac{1}{\Gamma(H + \frac{1}{2})} \left(\int_{-\infty}^0 \left[(t-s)^{H-\frac{1}{2}} - (-s)^{H-\frac{1}{2}} \right] dB(s, \omega) + \int_0^t (t-s)^{H-\frac{1}{2}} dB(s, \omega) \right)$$

Since the increments of the fBm are stationary, their variance scales as $\|h\|^2 H$; when t is in R^n , one has $H = nD$: In natural scene modeling, fBm's have been widely used as surfaces[1] whose roughness parameter is H . Unfortunately, there is no straightforward relationship between H and any structure, and the scaling law holds for a limited range of values of h only which makes the estimation of H very inaccurate. An IFS F is a set of mappings $(f_1, \dots, f_m)(m \geq 2)$ acting on non-empty compact subsets of R . A fundamental property of a contractive IFS is the existence of a unique attractor: $A = \bigcup_{i=1}^m f_i(A)$. This time, it is possible to compute F from some geometric structures extracted from the images but the features of the generated images remain very basic and regular. An improvement is Levy-Vehel's Generalized IFS (GIFS)[11] but as pointed out, one gets



FIGURE 1. Original grass (D9), bark (D12) and raffia (D84) textures of size 243×243 .

a good approximation of a set if it is nearly (with respect to some distance) fractal; if not, the parameters will be so numerous that the analysis becomes untraceable. Within the framework of radar analysis, Martinez [16] adapted Universal Multi-fractals [19] (i.e. continuous cascaded processes) to turbulence phenomena.

Any fractal approach makes use of the fractal dimension FD . For instance, Espinal[4] introduced a new definition of FD computed by wavelet analysis while in other papers, natural textures [9, 13] or medical textured images [14] are finitely approximated by fBm. In [8], Keller took into account lac unary and fractal dimension for natural texture modeling and segmentation. In [17], Peleg defined the fractal signature which provides spectral information on the textures. But whatever the dimension is, the metric yields a global characterization. In particular, different studies showed the improvement of segmentation results when considering local fractal dimensions [10, 15]. Chaudhuri and Sarkar proposed [3] a set of 6 metrics which are computed from fractal and Renyi's generalized dimensions.

In [12], Levy-Vehel and Mignot defined capacities for texture analysis based on the Multi-fractal spectrum; as for Renyi's generalized dimensions, the measure is defined regardless of the data. As a conclusion, we might say that if indeed Multi-fractal analysis seems suitable for texture modeling and analysis, some adaptation to the current application should be considered. In this paper, we present a Multi-fractal texture model which can be used in airborne and outdoor image segmentation. Since the object types occurring in this class of images are numerous, the model must be general but at the same time, its parameters identification must remain computationally tractable. In section 2, a new Multi-fractal measure is introduced. Section 3 deals with the suitability of the model to texture representation. Two "scale-stable" parameters, derived from the model parameters, are proposed for texture characterization and image segmentation. Finally, experimental results are shown in section 4.

2. MMM's: Multipermuted Multinomial Measures. In [7], we introduced the so-called *Multipermuted Multinomial Measure* (MMM) as a generalization of classical deterministic multinomial measures which are defined in the limit of multi-cascaded processes. Let us consider $C_0 = [0, 1) \times [0, 1)$ as the support of the MMM, namely $\mu\Pi_p$. The construction is based on an iterated splitting of C_0 combined with a multiplicative rule between two successive stages. More precisely, C_0 ($p(C_0) = 1$) is partitioned regularly into 2^2 subsets $C_{i,j}^1$ at the first stage. Each of them is simply a reduction of C_0 by a factor p fitted with a measure $P_{i,j}$ such that the total measure of these subsets is 1. At the next

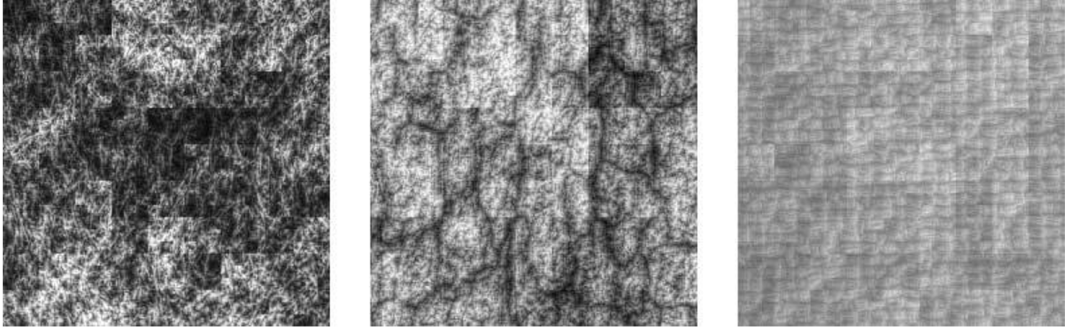


FIGURE 2. MMM approximation of natural textures computed with $p = 3$ and $n = 5$.

stage, the same splitting procedure is carried out over each $C_{i,j}^1$ leading to $(p^2)^2$ subsets C_{k_i,l_j}^2 whose measure is defined by a recurrent multiplicative rule:

$$\forall n \geq 1, \mu \Pi_p \left(C_{k_i,l_j}^{n+1} \right) = P_{\pi_{i,j}^n(k,l)} \mu \Pi_p \left(C_{i,j}^n \right) \quad (1)$$

where $k_i = k + \lfloor (i+1)/p \rfloor$ and $l_j = l + \lfloor (j+1)/p \rfloor$, ($\lfloor x \rfloor$ denotes the integral value of x); $\pi_{i,j}^n$ is a permutation related to each subset $C_{i,j}^n$ at the stage n , its role is to permute the position of the measures $P_{i,j}$ for the multiplicative rule involved at the next stage. One gets the MMM by iterating. We must notice that if all the permutations are equal to the identity function, the limit measure corresponds to a classical multinomial measure. Multi-fractal analysis of a cascaded process is usually achieved by means of a repartition function $\Gamma(q, \tau)$ [6]. Since the permutations do not change Γ , one gets[7]:

$$\Gamma(q, \tau) = \lim_{n \rightarrow +\infty} \left(1 + \sum_{k=0}^{p-1} \sum_{l=0}^{p-1} \frac{P_{k,l}^q}{p^{2\tau}} \right)^n \quad (2)$$

The Multi-fractal behavior of a MMM is thus fully characterized by the Rnyi exponent $\tau(q)$ which is the unique function such that $\Gamma(q, \tau)$ converges to a non-vanishing value (equal to 1). According to their definition, MMM's are self-similar measures whose properties can be revealed either by the Hausdorff, or the Legendre, or the large deviations spectrum [5]. In fact, this assumption allows us to consider that a MMM has at least the same Multi-fractal properties as the related multinomial measure with the same parameters p and $P_{i,j}$. The inverse problem of parameters identification has been addressed in [7]. In brief, if the free parameter p is known, all the parameters (i.e. the measures $P_{i,j}$ and the permutations) of the MMM model can be estimated by using equation (1) successively from the finest resolution (pixels) to the coarsest one (image).

3. Natural texture representation. Experiments showed that $p = 3$ yields a relevant approximation and a good discrimination of natural textures as well. This is the value being used in the following. Figure 1 (resp. 2) shows the grass (D9), bark (D12) and raffia (D84) textures of the Brodatz album (resp. the MMM approximations). Despite a few artifacts due to the deterministic construction of the model, one can see that both the structures and the low-level information are well preserved. More precisely, the model fits well unstructured microscopic texture (like grass), macroscopic texture (like bark) as well as the structured microscopic texture (like raffia). This impressive adaptation ability is mainly due to the effect of the permutations which introduce a kind of randomness in the deterministic multiplicative rule.

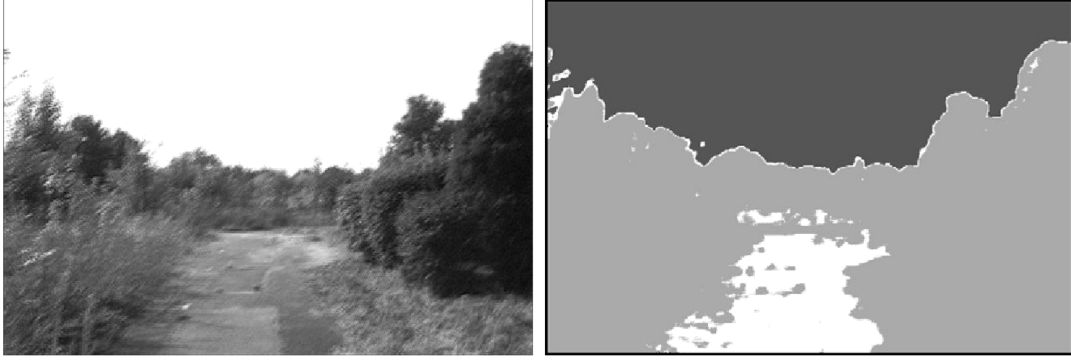


FIGURE 3. A blurred non structured road image and its segmentation result

Similar computations have been performed on other Brodatz and natural textures with similar visual qualities. The outstanding results demonstrate the relevance of the MMM model for natural texture approximation.

4. Automatic image segmentation for robot vision. Our model has been successfully applied to the automatic segmentation of a video stream. The video camera is on the top of a small autonomous vehicle and the segmentation process distinguishes the trail from the bush. For image segmentation purposes, a couple of Multi-fractal attributes are defined from the parameters of the MMM:

$$\alpha_{min} = -\frac{\log \left(\max_{i,j} P_{i,j} \right)}{2 \log p}, \quad \alpha_{max} = -\frac{\log \left(\min_{i,j} P_{i,j} \right)}{2 \log p} \quad (3)$$

Which are the minimum and maximum singularities of the set of local Hlder exponents [5]. Their choice is motivated by their scale-invariant property which is convenient for characterizing the structures occurring at the different scales of real world images. Given an image I to be processed, our new unsupervised segmentation algorithm consists of the following steps:

- a. Compute $(\alpha_{min}, \alpha_{max})$ within a 9×9 window centered at each pixel of I ;
- b. Estimate the smoothed histogram of the spatial distribution of the attributes ;
- c. Inverse the smoothed histogram such that the modes appears as basins ;
- d. Apply a watersheds technique [2, 20] on the inversed histogram for getting a partition of the attribute space ;
- e. Cluster the pixels according to this partition ;
- f. Regularize I by removing non- significant clusters (less than 5% of the pixels).

The smoothed histogram of the attributes has been computed with a resampling step equal to 0.003 and a smoothing factor (width of the filtering kernel) of 0.015. The watersheds algorithm yielded 4 clusters corresponding to the sky, the plants, the road and an un-significant one which has been removed by the regularization procedure. One can see the pixel accuracy of the method on an excerpt from the stream on the right of figure 3. The same segmentation has been achieved on the unprocessed 140 images of the stream (which are blurred due to the movement of the camera) with the same parameters for histogram computation. The results remain stable and accurate during the whole sequence.

5. Conclusion. We have introduced a fully automatic image segmentation algorithm based on a multi-fractal approximation model called Multi-permuted Multinomial Measures (MMM). The key point of this model is to take into account both numerical data and

structural information, allowing the approximation of either deterministically or statistically self-similar measures fitted with macroscopic and microscopic spatial distribution law. The computation of the model parameters from images allows their characterization and thus an accurate segmentation. The discussed segmentation algorithm consists in discretizing the spatial distribution of a couple of Multi-fractal attributes and in labeling within the image the pixels according to them. This is a rather classical approach indeed, the tremendous results we computed are mainly due to the good properties of the Multi-fractal model. As a conclusion, it is important to notice that the model is rather general, at least for textures. The images may be heterogeneous as the model can deal with patchworks of various textures and regular patterns. Other type of images may be processed, with various results. The model parameters computation is about 104 faster than any other existing algorithm. One of the improvements of the present algorithm may consist in its generalization to 4D images, allowing real video processing.

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